Urban Forestry & Urban Greening 60 (2021) 127062

Contents lists available at ScienceDirect

Urban Forestry & Urban Greening

journal homepage: www.elsevier.com/locate/ufug

# An uncertainty framework for i-Tree eco: A comparative study of 15 cities across the United States

Jian Lin [a,*], Charles N. Kroll [b], David J. Nowak [c]

[a] Graduate Program in Environmental Science, State University of New York College of Environmental Science and Forestry, Syracuse, NY, 13210, USA
[b] Department of Environmental Resources Engineering, State University of New York College of Environmental Science and Forestry, Syracuse, NY, 13210, USA
[c] USDA Forest Service, Northern Research Station, Syracuse, NY, 13210, USA

ARTICLE INFO

Handling Editor: Richard Hauer

*Keywords:*
Bootstrap
Ecosystem services
Model uncertainty
Monte carlo
Urban forestry

ABSTRACT

Uncertainty information associated with urban forest models are beneficial for model transparency, model development, effective communication of model output, and decision-making. However, compared with the extensive studies based on the applications of urban forest models, little attention has been paid to the uncertainty of the output from these models. In this study, bootstrap and Monte Carlo simulation were employed to explore the uncertainty of i-Tree Eco. We assess the uncertainties associated with input data, sampling methods and models throughout the processes of urban forest structure and function quantification, and we propagate and aggregate the three sources of uncertainty to derive an estimator of total uncertainty. The uncertainty magnitude is expressed as the coefficient of variation. By applying the uncertainty framework to a network of 15 cities across the United States, we find that the average magnitude of total uncertainty across 15 cities is 12.3 % for leaf area, 13.4 % for carbon storage, 11.1 % for carbon sequestration, 40.7 % for isoprene emissions, and 25.0 % for monoterpene emissions. For leaf and carbon estimators, the total uncertainty is primarily driven by sampling uncertainty; the magnitudes of all three sources of uncertainty are comparable across 15 cities. In contrast, input, sampling, and model uncertainties all contribute to the total uncertainty for isoprene and monoterpene emission estimators, and there are large variations in these three sources of uncertainty across the 15 cities. An analysis of a regression-based approach to estimate input and model error indicated only moderate improvements over using averages across sites when estimating total uncertainty.

## 1. Introduction

Modeling techniques have become increasingly popular in urban forestry, and a fundamental yet often overlooked characteristic of a model is its uncertainty (Wu et al., 2006). Uncertainty typically exists in every component of a model such as input data, model parameters, and model structure (Beck, 1987; Beven and Binley, 1992; Draper, 1995). The model building and calibration process (e.g., modeling assumptions, calibrating to datasets, communicating outputs, making decisions) could also introduce additional sources of uncertainty (Ascough Ii et al., 2008; Beven et al., 2015; Hallegatte, 2009; Helton et al., 2006). In addition, applying models to real world applications typically increases the magnitude of output uncertainty. Urban systems are particularly spatially complex heterogeneous areas where forest model applications may differ from those on which the models are based and developed (Hill, 1998). In addition, scale effects require re-verification of model structure and re-estimation of initial and boundary conditions and coefficient thresholds (Narasimhan et al., 2005; Rindfuss et al., 2004). Given these issues, uncertainty analysis (UA) should be regarded as important as model output, and the assessment of model output uncertainty should be formally integrated in modeling practices (Pappenberger and Beven, 2006; Gallagher and Doherty, 2007). Decision-makers may alter their management decisions with a better understanding of uncertainty of model output (Bryant et al., 2018; Walker et al., 2003).

While various methods of UA have been developed to identify and quantify different sources of uncertainties in many fields of environmental sciences (Clark, 2003; Held, 2005; Mishra, 2009), uncertainty in urban forest modeling has been limited (Lin et al., 2019). This limitation is probably due to the general complexity of urban forest models, the time and effort needed to perform a thorough uncertainty analysis, and the lack of guidance as to the best methods to assess urban forest model

* Corresponding author at: 321 Baker, 1 Forestry Dr., Syracuse, NY, 13210, USA.
*E-mail address:* jlin27@syr.edu (J. Lin).

https://doi.org/10.1016/j.ufug.2021.127062
Received 4 November 2020; Received in revised form 27 January 2021; Accepted 20 February 2021
Available online 25 February 2021

output uncertainty (Pappenberger and Beven, 2006; Refsgaard et al., 2007). UA is usually something added after a model has already been developed. For example, in models such as ENVI-met and the Green Cluster Thermal Time Constant, only model output uncertainty (or prediction error) is assessed and expressed as the discrepancy between model predictions and observations (Shashua-Bar and Hoffman, 2002; Wu and Chen, 2017). In addition, only specific kinds of uncertainties are typically assessed. For example, in i-Tree Eco, only sampling error of field plot data is evaluated while other kinds of uncertainties (e.g., model and input uncertainty) are ignored, resulting in an underestimation of overall uncertainty (Nowak et al., 2013). Most studies focus on examining output uncertainty from either a single case study and/or a single source of uncertainty (Nowak et al., 2008b). A comparative study across diverse social, ecological and climatic contexts is needed to more rigorously assess commonalities and ranges of output uncertainty. The extent to which the magnitudes of uncertainty are dependent on factors such as tree measurements, sampling size, and diversity of environmental conditions requires a thorough synthesis of case studies across different urban settings.

Models of urban forests have been developed to quantify the structure, function and ecosystem benefits provided by trees. i-Tree Eco (hereafter referred to as "Eco") (https://www.itreetools.org/), is a model that has been widely employed in urban forest decision making such as developing priority planting schemes (McPherson et al., 2011) and urban forest master plans (Leff, 2016), informing environmental regulatory issues (Nowak et al., 2014), assessing the tradeoffs among different kinds of ecosystem services (Bodnaruk et al., 2017), and the equality and equity of urban forest ecosystem services (Nyelele and Kroll, 2020). Uncertainty analyses increase the transparency and credibility of the modeling procedure and the associated model outputs and help facilitate the effective use of model outputs in urban forest decision-making. Without uncertainty information, users may incorrectly view model output as error free or incorrectly infer error magnitudes.

This study focuses on an UA of Eco. Currently the model only produces uncertainty estimates based on the impact of sampling uncertainty (Nowak et al., 2008a). To overcome the gaps and promote a better use of this tool, here we assess input, sampling and model structure uncertainties (Regan et al., 2002; Refsgaard et al., 2007; Yanai et al., 2018). These three sources of uncertainty are estimated, compared, and aggregated to derive an estimator of total uncertainty. Forest structure and function considered in this study include leaf area and biomass, carbon storage and sequestration, and biogenic volatile organic compound (BVOC) (isoprene and monoterpenes) emissions. The detailed processes to estimate those outputs can be found in the supplementary material (Eqns S1-S10). We perform the UA across 15 cities in the United States (US), explore ways to including input and model uncertainty in subsequent studies, and discuss implications on future urban forest plot inventory assessments, model development, and model-assisted decision-making.

## 2. Study sites and data employed

### 2.1. Study sites

This study examined a network of 15 cities located in 14 states that have available urban forest inventory field plot data (Fig. 1). The study sites are spread across the US and cover diverse social and ecological settings. The cities have a range of size and climatic conditions, and arid, boreal and temperate systems are represented. The characteristics of the study sites are summarized in Table 1, which includes the average annual precipitation and temperature, and city size.

### 2.2. Field data

Field data were sampled and collected based on the Eco protocols developed by the USDA Forest Service (i-Tree Eco Field Guide, 2019). In each city, circular one-tenth acre plots were established across the entire

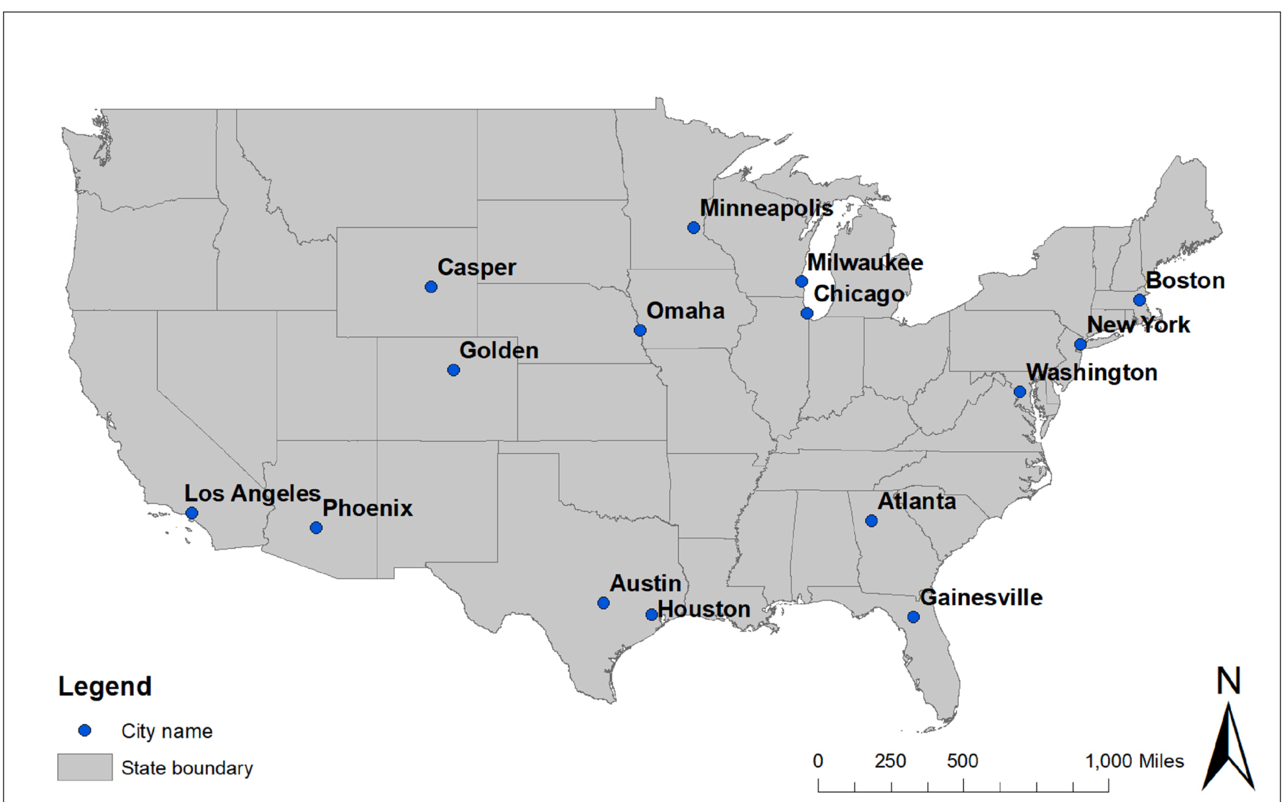


**Fig. 1.** The distribution of 15 cities examined in this study.

**Table 1**
The sampled plot and tree information for 15 cities.

| City, State | Average annual precipitation (cm) | Average annual temperature (°C) | City size (ha) | Year | No. sampled plots | No. sampled trees | Species richness[a] | DBH range (cm) | Tree canopy cover (%) |
|---|---|---|---|---|---|---|---|---|---|
| Atlanta, GA | 119.6 | 16.3 | 34,139 | 1997 | 205 | 2506 | 93 | 2.5–130 | 36.8 |
| Austin, TX | 87.1 | 20.8 | 158,013 | 2015 | 207 | 2553 | 62 | 2.5–185 | 30.8 |
| Boston, MA | 112.3 | 9.8 | 14,279 | 1996 | 217 | 955 | 82 | 2.5–144 | 22.3 |
| Casper, WY | 31.8 | 7.4 | 5466 | 2006 | 234 | 235 | 47 | 2.5–116 | 8.93 |
| Chicago, IL | 84.3 | 9.8 | 59,805 | 2007 | 745 | 1795 | 102 | 2.0–116 | 19.4 |
| Gainesville, FL | 120.4 | 20.4 | 12,174 | 2007 | 93 | 1414 | 84 | 5.1–241 | 50.6 |
| Golden, CO | 62.2 | 4.1 | 2447 | 2007 | 115 | 196 | 60 | 2.5–80 | 11.4 |
| Houston, TX | 115.1 | 20.6 | 173,270 | 2004 | 332 | 2001 | 68 | 12.7–128 | 23.6 |
| Los Angeles, CA | 47.5 | 17.7 | 121,774 | 2007/08 | 348 | 685 | 139 | 2.5–114 | 14.1 |
| Milwaukee, WI | 87.4 | 8.7 | 25,057 | 2008 | 216 | 1169 | 82 | 2.5–114 | 21.6 |
| Minneapolis, MN | 77.2 | 9.4 | 15,112 | 2004 | 110 | 282 | 41 | 2.5–117 | 26.5 |
| New York, NY | 117.3 | 13.3 | 78,647 | 2013 | 296 | 1075 | 139 | 2.5–122 | 18.5 |
| Omaha, NE | 77.7 | 10.6 | 29,873 | 2008/09 | 189 | 1005 | 26 | 2.5–145 | 21.2 |
| Phoenix, AZ | 20.4 | 23.9 | 134,701 | 2013 | 204 | 270 | 65 | 2.5–89 | 9.00 |
| Washington, DC | 119.6 | 13.2 | 15,915 | 2004 | 201 | 1002 | 106 | 2.2–180 | 28.6 |

[a] number of tree species measured.

city area using simple random sampling, and tree species, diameter at breast height (DBH), tree height, crown height and width, tree condition, crown light exposure (CLE), and percent leaf dieback were measured (Nowak et al., 2008a). DBH is estimated at 1.37 m above the ground using a DBH tape. All woody species with a minimum DBH of one-inch were measured. Tree height is measured as the height from the ground to the top of the tree. Crown height is equal to the height difference between the live top of the tree and the crown base while crown width is the average of the widths of the crown in the north-south and east-west directions. The crown diameters were measured by clinometer or laser device. Tree condition (crown dieback) is estimated based on the percent of the crown that is composed of dead branches with 5 percent classes. CLE is the number of sides of the tree receiving sunlight from above (ranging from 0 to 5), which is employed to estimate competition and consequently growth rates. The number of field plots varied by city, ranging from 93 plots in Gainesville, FL to 745 plots in Chicago, IL (Table 1). Inside each plot, the number of inventoried trees also show a large variability, varying from 0 (which occurs when plots fall within non-vegetative areas that have no trees) to 71 trees.

### 2.3. Environment data

We obtained weather variables from the National Solar Radiation Database (NSRDB) (https://nsrdb.nrel.gov/). The weather variables considered in this study included temperature and solar radiation. The NSRDB consists of several serially complete collections of hourly and ½ hour values of meteorological data, including the Physical Solar Model (PSM) and the Meteorological Statistical Model 3 (MTS3). Although the MTS3 has a total of 1454 stations across the US, it still provides limited coverage for our study sites. To fully capture the spatial variability of meteorological data, we employed the PSM. The PSM covers the US from 1998 to 2018, and has a temporal resolution of ½ hour and horizontal resolution of 4 km. The dataset is developed using a physical model, satellite products, and meteorological station data, and is updated over time as better technologies and new data sets become available (Habte et al., 2017; Sengupta et al., 2018). We downloaded the weather variables inside the city administrative boundaries for the same year when the field data were collected for each city, and converted the ½ hour data to hourly data by averaging. We ran our simulation at an hourly time step using weather data for July of that year, which is typically the hottest month of the year in the US. For Atlanta, GA and Boston, MA, the plot data were collected in 1997 and 1996, respectively. We used the PSM data in 1998, the earliest available dataset, in these two cities.

## 3. Methods

Three sources of uncertainties (e.g., input, sampling and model uncertainty) were evaluated in this study. Assuming the independence of these three sources of uncertainty, we also aggregated them to derive an estimator of total uncertainty. Since the most pressing social-ecological problems and the associated decision-making (e.g., policy formulation and urban forest master plans) are typically addressed at the landscape scale, the uncertainty of Eco outputs was assessed based on the total estimate per unit land area (e.g., carbon storage (Mg)/hectare, leaf area ($m^2$)/ hectare) rather than based on individual trees. We employed the coefficient of variation (CV), the variance of an estimator divided by its mean value, as an indicator of uncertainty magnitude. CV is the relative variability of an estimator, a unitless quantity which has been employed to examine uncertainty magnitude in other studies (Hanna et al., 2005; Yanai et al., 2010). CV is more convenient than variance as a measure uncertainty because it allows us to compare uncertainty among different Eco outputs with varying units and ranges.

### 3.1. Input uncertainty

Sensitivity analyses were previously performed to investigate the relationships between input and output variables in Eco and to identify the most important parameters for estimating urban forest structure and function (Lin et al., 2020; Pace et al., 2018). For leaf area (LA) and leaf biomass (LB) estimators, Lin et al. (2020) identified crown height and width to be the most important variables; for BVOC emission estimators, leaf biomass, temperature, and photosynthetically active radiation (PAR) were most important; and for carbon storage and sequestration estimators, DBH was most important. We represented input uncertainty of tree attributes (e.g., DBH, crown height and width) and meteorological data (e.g., temperature and PAR) in different ways.

For tree attributes, input uncertainty was represented as measurement error. Here the criteria of the USDA Forest Service's Forest Inventory and Analysis (FIA) national core field guide were adopted (https://www.fia.fs.fed.us/library/field-guides-methods-proc/). The core guide employs two criteria to indicate measurement quality: measurement tolerance (MT), that is the range of measurement that is acceptable, and measurement quality objective (MQO), that is the percentage of time that collected data are required to be within MT. Here we assumed that these FIA criteria are indicative of the measurement error of tree attributes. The FIA core guide states that the MT for tree height and compacted crown ratio (defined as the portion of the tree supporting live foliage) should be within +/- 10 % of the true length, and the MQO should be at least 90 % (meaning that crews are expected to be within the measurement tolerance at least 90 % of the time). Based on the MT (within +/- 10 % of crown height) and MQO (at least 90 % of repeated times) criteria, the probability distribution of measurement error of crown height was represented as:

$$P\ (\mu - 0.1\ \mu \leq\ \varepsilon\ \leq \mu + 0.1\ \mu) = 0.9 \quad (1)$$

where ε denotes the measurement error of crown height and $\mu$ is the mean of ε. From Eqn (1) and assuming measurement errors are well described by a normal distribution, we calculated the CV for ε as 0.0608. For the measurement error of crown width, the FIA core guide doesn't provide specific guidance. Here we assumed crown width measurement error follows a normal distribution with a CV that is similar in magnitude to the CV for crown height. To evaluate the sensitivity of the effects of measurement errors of crown width to CV magnitudes, CV values of 0.05, 0.075, and 0.01 were tested.

For DBH, the FIA core guide states that MT should be within +/- 0.1 inch per 20.0 inch increments of measured DBH, and MQO should be at least 95 %. Since DBH in the NYC plot data ranges from 1 to 47.9 inches, we have three MT values, +/- 0.1, +/- 0.2, and +/- 0.3, for DBH varying from 1 to 20, 20–40, and 40–47.9, respectively. Following similar procedure as those used to obtain measurement errors for crown height, we calculated measurement errors for the three DBH size groups with a standard deviation (SD) equal to 0.051, 0.102, and 0.153 in., respectively.

Eco uses a single monitoring station closest to the study area's geographic center for meteorological data. For meteorological data, spatial variability, as opposed to the variability of individual measurements, most likely dominates input uncertainty. We represented input uncertainty for meteorological variables as the spatial variability among the meteorological monitoring data downloaded from the National Solar Radiation Database (NSRDB) (https://nsrdb.nrel.gov/). Similar to the studies of Hanna et al. (2005); Zheng et al. (2010) and Situ et al. (2014), we assumed temperature (T) and PAR have normal distributions. The mean of T was derived by:

$$\mu_{i,j} = \frac{\sum_{k=1}^{N} T_{i,j,k}}{N} \quad (2)$$

where i is the day in July, j is the hour of the day, k is the station, and N is the total number of stations in the study area. The overall standard deviation (SD) of T (σ) was estimated as a function of the SD for a specific hour of the day ($\sigma_{i,j}$) where:

$$\sigma_{i,j} = \sqrt{\frac{\sum_{k=1}^{N} (T_{i,j,k} - \mu_{i,j})^2}{N-1}} \quad (3)$$

and

$$\sigma = \sqrt{\frac{\sum_{i=1}^{31}\sum_{j=1}^{24} \sigma_{i,j}^2}{31*24}} \quad (4)$$

As we ran our simulation on an hourly time step for the month of July at each study area, the denominator in Eqn (4) is 31 (days) * 24 (hours). We obtained the SD for input uncertainty of temperature by adjusting σ with the hourly temperature autocorrelation structure using an autoregressive model of order one (Salas, 1980):

$$\varepsilon_T = \varnothing_1 {}^* \varepsilon_{T-1} + \ \varepsilon_{\varepsilon_T} \quad (5)$$

where $\varepsilon_T$ is the input uncertainty of temperature at time T, $\varnothing_1$ is the lag-1 autoregressive parameter between two continuous time periods T and T-1 which is derived from the hourly temperature data from all available monitoring stations, and $\varepsilon_{\varepsilon_T}$ is a random error term of the input uncertainty of temperature which is assumed to be normally distributed with a mean of 0 and a standard deviation of σ. A thousand sequences of $\varepsilon_T$ were then simulated for the month of July, and the CV of model outputs across all one thousand simulations were calculated. The mean and SD values for input uncertainty of PAR were estimated in a similar manner as temperature.

### 3.2. Sampling uncertainty

We also evaluated the effects of sampling uncertainty, based on the number and distribution of plot data, on model output estimators using a bootstrap simulation, a resampling technique (Efron, 1982). Specifically, for each city, we repeated the following steps to calculate sampling uncertainty magnitudes (indicated by CV) for six Eco output variables (leaf area and biomass, carbon storage and sequestration, and isoprene emissions, and monoterpene emissions): (1) we resampled the entire number of plots in each city with replacement to produce 1000 input datasets; (2) we applied the 1000 input datasets to Eco to calculate 1000 estimates for the six Eco variables; (3) we calculated the standard deviation and mean values across the 1000 outputs for the six variables; and (4) we calculated CV values based on the standard deviation and mean for each of the six variables. In addition, we examined the impact of increasing sampling size on uncertainty magnitude using the Chicago site as a case study. The Chicago site has 745 plots, which is the largest number across our 15 cities. We resampled a increasing number of plots (25, 50, 100, 200, 300, 400, 500, 600 and 745), and repeated the above bootstrapping procedure to calculate uncertainty magnitudes for the six Eco variables under each plot number scenario. The bootstrap resampling is again repeated 1000 times.

Note that the sampling uncertainty could also be estimated directly from the data as is currently done in i-Tree Eco (standard deviation of estimator across plots/(number of plots)$^{1/2}$). The bootstrap resampling provides a convenient method to verifying these results and also allows us to assess the symmetry of confidence intervals derived from the sampling uncertainty.

### 3.3. Model uncertainty

The Eco estimators of LA, LB, and carbon storage and sequestration are based on empirical allometric regression models. We represented model uncertainty as model fitting error; model selection uncertainty was not addressed in this analysis. The model fitting error was derived based on the variance-covariance matrix for the intercept and slope coefficients (V-C):

$$V - C\ = \sigma^2 (X^{'} X)^{-1} \quad (6)$$

where $\sigma^2$ is the mean square error (MSE) associated with each regression equation, and X denotes a matrix of model explanatory variables with a preceding column of 1 s representing the intercept term. In Eqn (6), we only had access to estimated MSE values associated with the original regression equations, and therefore we assumed that the data used to develop the equation had the same properties as the sampled field plot data (thus deriving X from the field plot data). If the residuals in the regression model are normally distributed (which is assumed), the parameter estimators are also normally distributed. Since the population variance of the residuals is unknown and estimated from the reported MSE, the parameter estimators follow a Student's t-distribution with the degrees of freedom as a function of the number of trees pertaining to each allometric model. Using the derived V-C matrix and a Student's t-distribution, we randomly obtained 1000 sets of model coefficients for each allometric model using MC simulation. We then applied the 1000 sets of model coefficients to the field plot data to calculate 1000 model outputs, from which the output CVs can be estimated.

BVOC emissions in Eco are estimated based on the procedures shown in Eqns (S3)-(S6) in the supplementary material, an approach which was also adopted by the Biogenics Emission Inventory System (BEIS) from the US Environmental Protection Agency (Hanna et al., 2005). Previous studies based on other models of BVOC emission estimators, such as previous versions of BEIS (Hanna et al., 2005), the Model of Emissions of Gases and Aerosols from Nature (Situ et al., 2014), and the Global Biosphere Emissions and Interactions System (Zheng et al., 2010), demonstrate that model parameters are key sources of uncertainty for BVOC emission estimators (Situ et al., 2014; Zheng et al., 2010). The uncertainty information (e.g., distribution, mean, and SD) of the main parameters (e.g., $c_{T1}$, $c_{T2}$, $T_M$, $c_{L1}$, $\alpha$, and β) in the Eco processes were obtained from the literature (Hanna et al., 2005). The meanings of the parameters and how they are employed to estimate BVOC emissions can be found in the supplementary material to this paper. Their statistical information and default values employed in Eco are summarized in Table 2. We then used MC to randomly sample parameter values from each distribution, and then estimated BVOC emissions with these parameter values. The CVs were then calculated using the output from the 1000 iterations.

### 3.4. Total uncertainty

In addition to estimating the input, model and sampling uncertainties for each Eco output estimator, we also calculated the total uncertainty as:

$$CV_{Total}=\frac{\sqrt{(CV_{Input}*Estimate)^2+(CV_{Model}*Estimate)^2+(CV_{Sampling}*Estimate)^2}}{Estimate} \quad (7)$$

where $CV_{Input}$, $CV_{Model}$ and $CV_{Sampling}$ are the CVs estimated for input, model and sampling uncertainty, respectively, and “Estimate” is the estimate (mean) of the model ecosystem service. Eqn (7) is obtained because the variance of a summation of random variables can be estimated by summing the variances of the individual random variables, as long as the random variables are independent (Devore, 2016). This approach was also implement by Yanai et al. (2020) for assessing the uncertainty of forest carbon estimators. In addition, the relationships between total uncertainty and three sources of uncertainty across 15 cities were examined. For leaf and carbon, the ratios between total and sampling uncertainty were calculated for different cities. For BVOCs, linear regression was performed for the input and model uncertainty for isoprene and monoterpene. Stepwise AIC (a stepwise regression process to identify a suitable set of explanatory variables from multiple-model comparisons based on the Akaike information criterion) was initially performed to develop a base model, and then variables with parameter estimator p-values greater than 0.05 were removed from the models. Using these developed models, a leave-one-out cross-validation was then performed where 1 study site was sequentially removed, the model was fit using data at the other 14 sites, and then the new model was used to predict the input or model uncertainty at the removed site. A similar leave-one-out cross-validation was also used to develop predictions from the average input and model uncertainty by removing 1 site, calculating the average of the other sites, and then using that average as the prediction at the removed site. The regression (and average) predictions were then used to estimate the CV of the total uncertainty ($CV_{Total,Reg}$) using Eqn 7. The performance of the regression and average estimators was assessed by calculating the average relative absolute difference (ARAD) for the regression estimator of CV of total uncertainty:

$$ARAD = 100^* \sum_{i=1}^{15} \frac{|CV_{Total\_Reg\_i} - CV_{Total,i}|}{CV_{Total,i}} \Big/ 15 \quad (8)$$

where $CV_{Total,\ i}$ is the estimate of the total uncertainty at the $i^{th}$ site from Table 5 and 15 is the number study sites examined. ARAD is a convenient and easily interpretable measure of the average percent difference of an estimator. A similar procedure was also used for the average predictions. The ARAD was calculated using only the regression (and average) estimators for input uncertainty (where the sampling and model uncertainty comes from Table 5), only the regression and average estimators for model uncertainty, and using both input and model uncertainty from regression and average estimators.

**Table 2**
Statistical information of main model parameters to estimate BVOC emissions.

| Parameter | Original value in Eco | Unit | Distribution | Mean | SD |
|---|---|---|---|---|---|
| cT1 | 95,000 | J/mol | Lognormal | 95,000 | 20,000 |
| cT2 | 230,000 | J/mol | Lognormal | 230,000 | 150,000 |
| TM | 314 | K | Normal | 314 | 3 |
| cL1 | 1.066 | dimensionless | Normal | 1.06 | 0.2 |
| α | 0.0027 | $m^2$*s/ μmol | Lognormal | 0.0027 | 0.0015 |
| β | 0.09 | 1/K | Lognormal | 0.09 | 0.02 |

## 4. Results

### 4.1. Leaf area (LA) and leaf biomass (LB) estimators

The uncertainty magnitudes for LA across 15 cities are displayed in Table 3. The uncertainty magnitudes were expressed as CV values. The uncertainty results for LB were very similar to the LA results, and thus not shown here. For LA, the magnitudes of total uncertainty across 15 cities averaged 12.3 %, and ranged from 8.1% to 18.5%. Sampling uncertainty was the primary contributor to total uncertainty; input and model uncertainties had much smaller impacts. The mean magnitudes for both input and model uncertainties of LA were 0.7 % and 2.0 % respectivelyacross all 15 cities, while sampling uncertainty averaged 12.2 % (Table 3). If the average input and average model uncertainty across all sites was employed to estimate the total uncertainty of LA, the ARAD for the total uncertainty of LA would be 1.7 %; as such, we recommend using the average input and model uncertainty, along with the site-specific sampling uncertainty, to estimate the total uncertainty for LA (and LB estimators).

Unlike the magnitudes of input and model uncertainties, which were relatively constant across the 15 cities, the magnitudes of sampling uncertainty varied greatly, ranging from 8.0 % (Chicago, IL) to 18.5 % (Austin, TX). To explore the variability of sampling uncertainty as a function of the number of plots, we employed the data from Chicago (with 745 plots) and bootstrap resampled from 25 to 745 plots and calculated the sampling uncertainty accordingly (Fig. 2). For LA, a decrease in sampling uncertainty from about 43 % (25 plots) to 8% (745 plots) was observed. Similar to results shown by Nowak et al. (2008b), the sampling uncertainty decreased sharply within the first 200 plots, and less so over 200 plots. Similar patterns were also observed for other

**Table 3**
Uncertainty magnitudes for leaf area.

| City, State | Leaf area (CV: %) | | | |
|---|---|---|---|---|
| | Input | Sampling | Model | Total |
| Atlanta, GA | 0.4 | 9.2 | 0.9 | 9.3 |
| Austin, TX | 1.6 | 18.5 | 0.5 | 18.5 |
| Boston, MA | 0.5 | 9.7 | 1.6 | 9.9 |
| Casper, WY | 1.1 | 15.2 | 2.4 | 15.4 |
| Chicago, IL | 0.4 | 8.0 | 1.1 | 8.1 |
| Gainesville, FL | 0.6 | 13.5 | 1.6 | 13.6 |
| Golden, CO | 1.1 | 17.1 | 4.0 | 17.6 |
| Houston, TX | 0.3 | 9.4 | 1.0 | 9.5 |
| Los Angeles, CA | 0.7 | 8.9 | 3.7 | 9.7 |
| Milwaukee, WI | 0.6 | 9.8 | 1.7 | 9.9 |
| Minneapolis, MN | 0.9 | 11.4 | 2.2 | 11.7 |
| New York, NY | 0.7 | 11.0 | 1.4 | 11.3 |
| Omaha, NE | 0.6 | 11.8 | 1.3 | 11.9 |
| Phoenix, AZ | 0.8 | 13.0 | 3.7 | 13.5 |
| Washington, DC | 0.7 | 14.1 | 2.4 | 14.3 |
| Mean | 0.7 | 12.0 | 2.0 | 12.3 |
| Standard deviation | 0.3 | 3.1 | 1.1 | 3.1 |

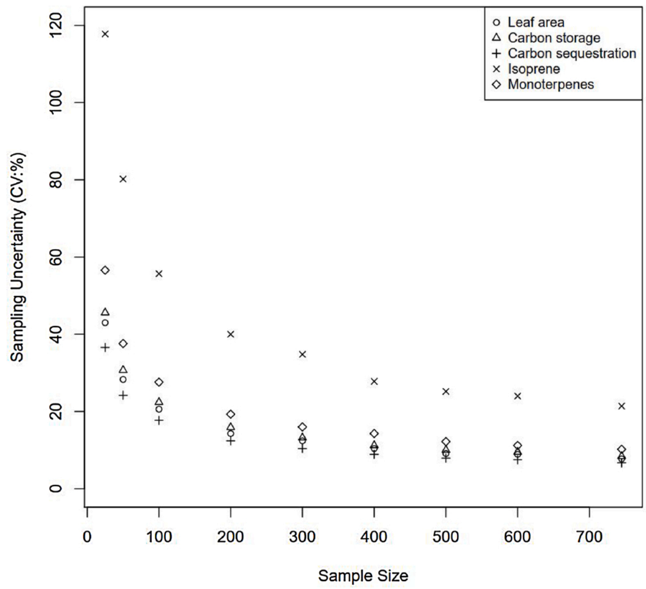


**Fig. 2.** The effects of plot numbers on magnitudes of sampling uncertainty in Chicago.

Eco outputs. Though not shown here, confidence intervals for the leaf area and biomass estimators derived from the bootstrap resampling were nearly symmetric, as is currently assumed in i-Tree Eco.

### *4.2. Carbon storage and sequestration estimators*

For carbon storage and sequestration, the average magnitudes of total uncertainty across 15 cities was 13.4 % (ranging from 9.3% to 19.5%) and 11.1 % (ranging from 7.9% to 15.4%), respectively (Table 4). The ranking of uncertainty magnitude was sampling > model > input. Sampling uncertainty played the dominant role, model uncertainty had a small influence, and input uncertainty had a negligible effect. Compared with input and model uncertainties, sampling uncertainty also had the largest variability across the 15 cities (Table 4), which again was primarily driven by different sample sizes across the cities (Fig. 2). Similarly to LA estimators, when using the average input and model uncertainty across all sites, the ARAD for the total uncertainty of carbon storage and sequestration estimators is small (1.3 % and 3.7 %, respectively), and thus we recommend using the average input and model uncertainty, along with the site-specific sampling uncertainty, to estimate total uncertainty.

### *4.3. Isoprene and monoterpenes emission estimators*

For BVOC emissions, the mean of total uncertainty was 40.7 % (ranging from 30.4% to 57.6%) for isoprene and 25.0 % (ranging from 16.7% to 32.9%) for monoterpenes (Table 5). The uncertainty magnitudes for BVOCs were much larger than for leaf and carbon estimators. All three sources of uncertainty played important roles for estimating total uncertainty of BVOC emissions. When examining the average values of uncertainty for isoprene, the order of uncertainty magnitudes was model (26.8 %) > sampling (23.8 %) > input (17.3 %); for monoterpene emissions, the order of average uncertainty magnitudes was sampling (17.6 %) > input (12.2 %) > model (11.1 %).

Unlike for LA and carbon estimators, where the input and model uncertainty contributed minimally to the total uncertainty, for BVOCs input and model uncertainty were larger contributors to the total uncertainty. While one could estimate the total uncertainty as a function of the at-site sampling uncertainty and the average of the input and model uncertainty across all the study sites, here we also explored whether regression models might be developed of input and model uncertainty for isoprene and monoterpenes as a function of the site characteristics in Table 1 to better estimate total uncertainty. The resulting regression models are presented in Table 6 which provide the parameter estimates with p-values in parentheses, and the model's adjusted coefficient of determination (Adj-$R^2$).

The leave-one-out cross-validation and ARAD results are presented in Table 7. Using average estimators of input and model uncertainty produces estimators of total uncertainty with an ARAD of 7.8 % for isoprene and 11.2 % for monoterpene; the regression estimators reduced the ARAD to 6.2 % and 5.5 %, respectively. While the regression estimators produced improved estimators of total uncertainty, the additional effort to obtain the regression model inputs for specific cities does not seem warranted, and it is recommended that average input and model uncertainty estimators from Table 5 be employed, along with study-specific sampling uncertainty, to estimate the total uncertainty of isoprene and monoterpene output from Eco.

We summarized the relationships among different Eco outputs and three sources of uncertainty based on the average CV values across 15 cities (Table 8). Overall, for leaf carbon estimators, their input and model uncertainties are low (< 5%), while their sampling and total uncertainties are moderate (between 5% and 20 %). For isoprene, model and sampling uncertainty is high (> 20 %) while input uncertainty is moderate. For monoterpenes, all sources of uncertainty are moderate except total uncertainty which is high.

**Table 4**
Uncertainty magnitudes for carbon storage and sequestration.

| | Carbon storage (CV: %) | | | | Carbon sequestration (CV: %) | | | |
|---|---|---|---|---|---|---|---|---|
| City, State | Input | Sampling | Model | Total | Input | Sampling | Model | Total |
| Atlanta, GA | 0.0 | 9.1 | 1.7 | 9.3 | 0.0 | 8.5 | 1.5 | 8.6 |
| Austin, TX | 0.0 | 10.0 | 0.5 | 10.1 | 0.0 | 7.9 | 0.7 | 7.9 |
| Boston, MA | 0.0 | 10.7 | 1.4 | 10.8 | 0.0 | 9.0 | 3.4 | 9.6 |
| Casper, WY | 0.1 | 19.1 | 4.2 | 19.5 | 0.0 | 14.6 | 3.2 | 15.0 |
| Chicago, IL | 0.0 | 8.7 | 3.9 | 9.5 | 0.0 | 6.8 | 5.9 | 9.0 |
| Gainesville, FL | 0.0 | 18.1 | 1.8 | 18.1 | 0.0 | 15.2 | 2.3 | 15.4 |
| Golden, CO | 0.1 | 18.1 | 2.5 | 18.3 | 0.0 | 15.3 | 1.4 | 15.4 |
| Houston, TX | 0.0 | 10.4 | 0.7 | 10.4 | 0.0 | 8.5 | 1.9 | 8.7 |
| Los Angeles, CA | 0.0 | 10.4 | 3.0 | 10.8 | 0.0 | 8.3 | 4.0 | 9.2 |
| Milwaukee, WI | 0.0 | 14.2 | 2.5 | 14.4 | 0.0 | 9.5 | 3.9 | 10.3 |
| Minneapolis, MN | 0.1 | 15.9 | 3.1 | 16.2 | 0.0 | 12.6 | 1.8 | 12.7 |
| New York, NY | 0.0 | 12.6 | 1.8 | 12.8 | 0.0 | 10.0 | 1.3 | 10.1 |
| Omaha, NE | 0.0 | 13.0 | 1.8 | 13.1 | 0.0 | 10.5 | 1.7 | 10.6 |
| Phoenix, AZ | 0.1 | 15.9 | 0.6 | 15.9 | 0.0 | 12.3 | 4.7 | 13.2 |
| Washington, DC | 0.0 | 12.1 | 1.7 | 12.2 | 0.0 | 9.9 | 1.3 | 10.3 |
| Mean | 0.0 | 13.2 | 2.1 | 13.4 | 0.0 | 10.6 | 2.6 | 11.1 |
| Standard deviation | 0.0 | 3.5 | 1.1 | 3.4 | 0.0 | 2.8 | 1.5 | 2.6 |

**Table 5**
Uncertainty magnitudes for isoprene and monoterpene emissions.

| | Isoprene emissions (CV: %) | | | | Monoterpene emissions (CV: %) | | | |
|---|---|---|---|---|---|---|---|---|
| City, State | Input | Sampling | Model | Total | Input | Sampling | Model | Total |
| Atlanta, GA | 16.2 | 11.2 | 23.4 | 30.5 | 12.0 | 10.0 | 5.8 | 16.7 |
| Austin, TX | 14.6 | 34.6 | 22.5 | 43.8 | 11.1 | 13.0 | 2.4 | 17.3 |
| Boston, MA | 17.3 | 17.9 | 31.6 | 40.3 | 11.8 | 13.8 | 17.9 | 25.5 |
| Casper, WY | 15.1 | 20.2 | 25.0 | 35.5 | 11.1 | 29.3 | 10.1 | 32.9 |
| Chicago, IL | 19.3 | 21.0 | 29.2 | 40.9 | 13.4 | 10.1 | 15.5 | 22.8 |
| Gainesville, FL | 14.1 | 17.7 | 23.6 | 32.7 | 10.3 | 15.4 | 6.0 | 19.5 |
| Golden, CO | 11.1 | 30.6 | 27.5 | 42.6 | 7.9 | 29.0 | 13.4 | 32.9 |
| Houston, TX | 16.2 | 11.3 | 23.1 | 30.4 | 11.8 | 15.4 | 5.2 | 20.1 |
| Los Angeles, CA | 23.4 | 17.0 | 26.5 | 39.2 | 16.5 | 15.4 | 12.4 | 25.8 |
| Milwaukee, WI | 16.6 | 26.9 | 31.1 | 44.4 | 11.4 | 14.8 | 17.4 | 25.5 |
| Minneapolis, MN | 16.1 | 45.3 | 31.6 | 57.6 | 10.6 | 19.7 | 17.8 | 28.6 |
| New York, NY | 16.9 | 18.3 | 26.0 | 36.0 | 11.9 | 19.0 | 11.5 | 25.2 |
| Omaha, NE | 33.0 | 30.2 | 28.1 | 52.8 | 18.0 | 16.4 | 13.9 | 28.0 |
| Phoenix, AZ | 12.9 | 37.9 | 27.0 | 48.3 | 12.9 | 26.1 | 7.2 | 30.0 |
| Washington, DC | 17.2 | 16.8 | 26.0 | 35.3 | 12.1 | 17.0 | 10.6 | 23.4 |
| Mean | 17.3 | 23.8 | 26.8 | 40.7 | 12.2 | 17.6 | 11.1 | 25.0 |
| Standard deviation | 5.2 | 10.0 | 3.1 | 7.9 | 2.4 | 6.1 | 5.0 | 5.1 |

**Table 6**
Regression model parameters of isoprene and monoterpene input and model uncertainty (p-values in parentheses).

| | Intercept | Temperature Average (K) | PAR Average (mol/ $m^2 \times s$) | PAR Standard Deviation (mol/$m^2 \times s$) | # Trees/ # Plot | Species Richness | Model Adj-$R^2$ (%) |
|---|---|---|---|---|---|---|---|
| Isoprene Input Uncertainty | 121 (0.052) | −0.480 (0.028) | 0.0191 (0.014) | 0.0506 ($5*10^{-5}$) | – | 0.0579 (0.026) | 78.2 |
| Isoprene Model Uncertainty | 179 (.003) | −0.507 (0.010) | – | – | −0.262 (0.069) | – | 54.7 |
| Monoterpenes Input Uncertainty | −10.5 (0.085) | – | 0.0117 (0.010) | 0.0234 ($2*10^{-4}$) | – | 0.0411 (0.009) | 66.3 |
| Monoterpenes Model Uncertainty | 327 ($2*10^{-5}$) | −1.05 ($3*10^{-5}$) | – | – | −0.410 (0.008) | – | 83.5 |

**Table 7**
Total Uncertainty ARAD for regression models and average of input and model uncertainty for isoprene and monoterpene.

| | Regression Input Uncertainty | Average Input Uncertainty | Regression Model Uncertainty | Average Model Uncertainty | Regression Input and Model | Average Input and Model Uncertainty |
|---|---|---|---|---|---|---|
| Isoprene Total Uncertainty | 3.6 % | 3.5 % | 3.7 % | 4.7 % | 6.2 % | 7.8 % |
| Monoterpene Total Uncertainty | 3.6 % | 3.3 % | 2.7 % | 9.1 % | 5.5 % | 11.2 % |

**Table 8**
A summary of relationship between Eco outputs and different sources of uncertainty.

| | Input | Sampling | Model | Total |
|---|---|---|---|---|
| Leaf area | Low[a] | Moderate[b] | Low | Moderate |
| Carbon storage | Low | Moderate | Low | Moderate |
| Carbon sequestration | Low | Moderate | Low | Moderate |
| Isoprene | Moderate | High[c] | High | High |
| Monoterpenes | Moderate | Moderate | Moderate | High |

[a] CV < 5%.
[b] 5% < CV < 20 %.
[c] CV > 20 %.

## 5. Discussion

### 5.1. Leaf area and leaf biomass estimators

Sampling uncertainty of LA dominated the other two sources of uncertainty, which resulted in the sampling uncertainty being approximately equal to the total uncertainty. The variability of sampling uncertainty was mainly due to sample size and the spatial variability of tree density. When the plot numbers in Chicago reduced from 745 to 25, the sampling uncertainty for LA increased from 8% to 43 %. The increased magnitude is likely a function of sampling intensity and study site heterogeneity. The sampling effects of LA are rarely evaluated, and the literature typically focuses on the influence of sampling on tree populations and tree's ecosystem services (Martin et al., 2013; Nowak et al., 2008b).

Model uncertainty for LA played a minor role (the mean CV = 2.0 %). This relatively low value may be due to model uncertainty being only represented as model fitting error. The regression equation for the LA estimator in Eco has a relatively good fit (R-square is 0.91 and MSE is 0.23) (Nowak, 1996). Therefore, when the intercept and slope coefficients were randomly sampled from the variance-covariance matrix developed based on a small MSE value, the differences among intercept and slope coefficients across the iterations were small. Apart from model fitting uncertainty, model selection can also be an important source of uncertainty (Yanai et al., 2018). The effects of model choices, such as comparisons among species-specific and multi-species models, and selecting extant foreign models or developing local models, are often evaluated in non-urban sites (Chave et al., 2014; Stas et al., 2017; Van Breugel et al., 2011). The current method adopted by Eco for the LA estimator is based on a crown-based allometric equation developed from park tree data in Chicago (Nowak, 1996). Other approaches to estimate

LA have also been developed, including species-specific equations (McPherson et al., 2016) and DBH-based equations (Timilsina et al., 2017). Comparisons among these methods are available in the literature. For example, by comparing four methods at a site located at northern California, Peper and McPherson (2003) reported that Nowak (1996) method tends to slightly overestimate LA. Another study, based on 74 urban trees and 5 species collected in Stevens Point, Wisconsin, concluded that locally developed LA models have higher accuracies than the default models employed by i-Tree Eco (Timilsina et al., 2017). However, these comparisons are typically constrained to limited species and single study sites. Future studies based on more representative datasets and systematic comparisons are needed. Locally developed allometric relationships are generally superior only if they are developed using a sufficiently intensive and representative data set (Van Breugel et al., 2011), but their development will substantially increase the cost of analyses. The reported low magnitude of model uncertainty does not indicate that model uncertainty can be ignored. This study only examined model fitting uncertainty and not model selection uncertainty; therefore, the reported model uncertainty for leaf area is most likely conservative.

Input uncertainty due to measurement errors of crown width and height is negligible at the landscape scale when compared with sampling uncertainty. Measurement errors are likely to be larger for individual trees, especially for large trees due to the exponential relationship in the allometric equation (Eqn S1). We adopted the FIA core criteria of measurement tolerance and measurement quality objectives, which are most appropriate for experienced professionals. Urban forest programs often employ citizen science to collect tree attribute data (Roman et al., 2017). When there is a lack of training and experience and the FIA measurement guidance is not strictly followed, input uncertainty may increase.

Based on the analysis performed, it is recommended that the average input and model uncertainty from Table 5 be employed along with a study-specific estimator of sampling uncertainty to estimate the total uncertainty (Eqn 7) of LA estimator from Eco. In most situations, the total uncertainty will be nearly identical to the sampling uncertainty.

### 5.2. Carbon storage and sequestration estimators

The largest uncertainty source for carbon storage and sequestration came from the sampling process, with the mean CV across 15 cities being 13.4 % and 11.1 %, respectively. The total uncertainty was approximately equal to the sampling uncertainty due to the dominating influence of sampling uncertainty. This sampling uncertainty had similar magnitudes as those found for LA, which is probably because they are influenced by the similar spatial heterogeneity of the tree population. There are only limited efforts in the literature that evaluate the effects of sampling intensity on ecosystem service outputs in urban sites. Nowak et al. (2008b) reported that 200 plots are needed to yield a 12 % relative standard error on the total number of trees based on field studies in 14 U. S. cities. Martin et al. (2013) found that in order to achieve a +-10 % error, 258, 870, and 483 plots are needed for the estimators of the number of trees, carbon storage and sequestration, respectively. McPherson et al. (2013) reported that standard errors for carbon storage and sequestration estimators are typically within 5–15% based on studies in Los Angeles and Sacramento, CA. Our average sampling uncertainty was 13.2 % across the 15 study sites, which is comparable to the values reported in these three studies. However, to achieve a comprehensive understanding of sampling uncertainty, it is necessary to incorporate the effects of other aspects of sampling strategy (e.g., sampling method), and to perform cross-site comparative studies to evaluate how city characteristics (e.g., city size and heterogeneity) influence sampling uncertainty.

The mean model uncertainties for carbon storage and sequestration estimators across 15 cities were 2.1 % and 2.6 %, respectively. Both carbon and LA are estimated based on regression equations. While the equations have different MSE values (0.054 and 0.232) for carbon and LA, this disparity had little effect on the resulting magnitude of model uncertainty for carbon and LA (CV = 2.0 %). Similar to the LA model, the magnitude of model uncertainty in the carbon model is also likely to be conservative due to the simplifying assumptions we made for Eqn (6), and the fact that only model fitting error was considered.

Several models have been developed to calculate carbon storage and sequestration, including those employed by Eco, i-Tree Streets, the CUFR Tree Carbon Calculator, and the Urban Tree Database biomass allometries, and some variability is reported when the models are compared (Aguaron and McPherson, 2012; Boukili et al., 2017). However, this variability typically results from different models employed (McHale et al., 2009) (i.e. applying different models to the same tree results in different estimates), which makes model selection an important uncertainty source. In the urban forestry field, model selection is further complicated by employing either urban-specific allometric equations, which are relatively scarce, or forest-derived equations with a correction factor for urban open-grown trees. As suggested by Davies et al. (2013) and McHale et al. (2009), standardizing the models and methods used to estimate carbon storage and sequestration may reduce variability and facilitate improved inter-city comparisons of these estimators. Other aspects of model uncertainty not considered in this study include species composition and species assignment errors (McPherson et al., 2013). Species misidentification may result in an assignment of inappropriate allometric equation. Depending on the species composition of a site, different proportions of the trees may be non-matching (i.e. there are not species-specific equations available), which necessitates the use of average results from models of the same genus (Nowak et al., 2008a). A higher proportion of non-matching sample site trees may increase the magnitude of uncertainty.

For input uncertainty, although DBH is identified as the most important variable for carbon storage and sequestration estimators of individual trees (Lin et al., 2020), the effect of small amounts of DBH measurement uncertainty on model output variability at the landscape scale is negligible. This minimal effect is probably because we adopted the FIA core guide criteria. The assumed magnitudes of input uncertainty due to the measurement errors are relatively small, which results in a small impact on output uncertainty.

Based on the analysis performed, it is recommended that the average input and model uncertainty from Table 5 be employed along with a study-specific estimator of sampling uncertainty to estimate the total uncertainty (Eqn 7) of carbon storage and sequestration estimators from Eco. Similar to LA, in most situations the total uncertainty would be nearly identical to the sampling uncertainty.

### 5.3. Isoprene and monoterpenes emission estimators

BVOC emissions are typically calculated by multiplying genus-based standardized emission rates by LB weights, and then correcting for environmental effects (Eqn S3). Commonly employed models for estimating BVOC emissions include Eco, BEIS, GloBEIS, and MEGAN (Wang et al., 2016). In Eco, a genus base emission rate database has been developed based on the literature (Nowak et al., 2006), and two environmental correction processes have been built for isoprene (temperature- and light-dependent (Eqns S4-S5)) and one for monoterpenes (temperature-dependent (Eqn S6)) emission estimators (based on BEIS processes).

For both isoprene and monoterpenes emissions, the total uncertainty is larger than that of the LA and carbon models due to increased input and model uncertainty. The increased model uncertainty is due to an increase in the number of model input variables and the increased input uncertainty is due to meteorological inputs (i.e., temperature and cloud cover/light) that can have relatively high variability among monitors. This finding is consistent with uncertainty assessments based on other BVOC emission models (Hanna et al., 2005; Situ et al., 2014). Apart from temperature and PAR, in other models additional environmental variables (e.g., humidity and wind speed) are also incorporated in BVOC emission estimators (Situ et al., 2014; Wang et al., 2016). It is not clear how these additional variables and associated processes affect the accuracy of BVOC emission estimators. The reduction of the uncertainty magnitude is not guaranteed unless the added processes are well-understood, well-represented and supported by good data (Turner and Gardner, 2015). Inter-model comparisons across different landscapes are beneficial to improving mechanistic understanding of BVOC processes, and to reduce input and model impacts on output uncertainty.

Compared with the effects of temperature, the uncertainty due to tree attributes (e.g., leaf biomass) is negligible. However, this doesn't mean that BVOC emission estimators are totally driven by environmental variables as tree attributes play a minor role. Through a sensitivity analysis, genus and leaf biomass were identified as the two most important input variables for estimating BVOC emissions (Lin et al., 2020; Pace et al., 2018). Input errors impacting LB estimators are likely due to small measurement errors of crown width and height, which limits the impact on output uncertainty. Treating all uncertainties probabilistically is impractical, and some uncertainty sources, such as nominal variables (e.g., genus), are not amenable to quantification (WHO, 2008). For low and high VOC-emitting genera, the differences in base emission rates can be up to a factor of 70 for isoprene, and 8 for monoterpenes (Nowak et al., 2006). The misidentifications of genera could also be a potential source of uncertainty. The i-Tree Database provides a mechanism for users to upload and employ local species-specific information. Advancements in science may not guarantee the reduction of some sources of uncertainty, such as those due to genera misidentifications. An effective approach is to develop a comprehensive local database which captures the diversity of the urban landscape.

Sampling uncertainty for both isoprene and monoterpenes emissions are larger than that for LA or carbon. This difference is probably because BVOC emissions are not only affected by the spatial heterogeneity of tree population, but also the spatial distribution of tree species. High and low VOC-emitting species may be unevenly spaced, such as when some plots are dominated by high-emitting species while others are dominated by low-emitting species. This results in large BVOC emission ranges across the sample plots and more sampling uncertainty.

Unlike for LA and carbon storage and sequestration, the input and model uncertainty of isoprene and monoterpenes was a large contributor to total uncertainty. Here a regression-based approach was used to assess whether estimators of input and model uncertainty could be estimated from site-specific field data. Our analysis showed that while the regression estimators were an improvement over using average estimators of input and model uncertainty, the improvements were relatively small and thus did not warrant the effort to obtain regression model inputs at new study sites. As such, it is recommended that the average input and model uncertainty from Table 5 be employed along with a study-specific estimator of sampling uncertainty to estimate the total uncertainty (Eqn 7) of isoprene and monoterpene estimators from i-Tree Eco.

### *5.4. Reducing estimator uncertainty*

The two most likely ways to reduce estimator uncertainty are in the model inputs and sampling. While input uncertainty is relatively low, efforts to ensure accurate field data collection are essential. Errors in tree measurements (e.g., DBH and crown diameters) will affect results such as leaf and carbon estimators. For estimators that require external environmental inputs (e.g., BVOC estimators), the number and proximity of these data to the trees being modeled will affect model outputs. These hourly environmental data (e.g., meteorological data) are spatially limited in most landscapes, but can vary substantially across landscapes. Efforts to obtain more spatially distributed data would help improve local estimators and reduce their uncertainty. However, given the practical and economic limitations in establishing more monitors, this limitation is not likely to be easily overcome and model inputs will continue to rely on the best available local environmental data.

Sampling errors were the dominant source of estimator uncertainty for most output variables and could be reduced by increasing the number of field plots used as model inputs. However, given the cost of field data collection and the diminishing return of reduced uncertainty with more field plots (e.g., Fig. 2, Nowak et al., 2008b), it is unlikely that many cities will establish more than 200 one-tenth acre field plots. The 200 plots were originally established based on the estimated number of plots that a field crew of two can collect in a summer season in a city. The 200 plot total produces a relative sampling uncertainty of around 12 percent for total number of trees (Nowak et al., 2008b), leaf area (Table 3) and carbon (Table 4), with a total uncertainty also around 12 percent.

Reducing the sampling uncertainty will reduce total uncertainty, but the cost of reducing this uncertainty with more plots and the relatively low uncertainty of about 12 % for many estimators will likely limit expanded field data collection to reduce uncertainty. Increasing the plot totals from 10 to 200 reduces relative uncertainty from around 50 percent to 12 percent; adding an additional 200 plots only reduces the uncertainty to around 8 percent, while likely doubling data collection costs. While reducing uncertainty is important, the costs of reducing uncertainty needs to be considered as well as whether the uncertainty needs to be reduced.

A 12 % total uncertainty for many urban forest estimators is likely an acceptable level of uncertainty for a population estimator. However, sub-population estimators (e.g., estimators for one species or within an individual land use) will have increased uncertainty due to increase sampling errors from a smaller sample size. If particular areas or species need to be assessed, the sampling strategy may need to be modified to reduce estimator uncertainty. Individual tree management (e.g., street trees) estimators often requires reduced uncertainty, and entire street tree populations are often inventoried (a census), reducing sampling error to zero. Users need to consider project goals, accuracy, uncertainty and costs when developing data collection and analysis protocols.

## 6. Conclusions and future directions

This study developed a framework to quantify the magnitudes of input, sampling, and model uncertainties on i-Tree Eco estimators of urban trees form and function, and applied the framework to 15 cities across the US. We found that the average magnitude of total uncertainty across the 15 cities was 12.3 % for leaf area, 13.4 % for carbon storage, 11.1 % for carbon sequestration, 40.7 % for isoprene emissions, and 25.0 % for monoterpene emissions. For leaf and carbon estimators, the magnitudes of all three sources of uncertainty relative to the total uncertainty are comparable across the 15 cities, while there are large variations in these three sources of uncertainty for BVOC emissions. We recommend employing the average input and model uncertainty, along with a site-specific estimator of the sampling uncertainty, to derive the total uncertainty of i-Tree Eco of leaf, carbon and BVOC estimators.

Uncertainty analysis should become a formal practice and necessary component of modeling exercises, especially for models which aim to support decision-making and policy-formation. Although this study performed a thorough uncertainty assessment for i-Tree Eco, it is worth noting several limitations of the study. First, uncertainty magnitudes reported in this study are still believed to be conservative due to the omission of other factors that could increase output uncertainty. Second, this study focuses on urban areas in US, and the applicability of findings to other locales especially outside US is uncertain. To reduce overall uncertainty, future studies could (1) develop urban- and species-specific allometric relationships when they are not available, (2) improve the spatial representation of meteorological weather monitors, (3) break the study domain into subareas when multiple monitors are available to improve local meteorological estimates, and (4) improve sampling strategies to ensure representation of the diversity of the urban forest, balancing sampling intensities and data collection costs. Intercomparisons among models are also beneficial assuming model mechanisms are well-understood, and the comparisons should be based on large sample sizes and multiple and diverse study sites.

## CRediT authorship contribution statement

**Jian Lin:** Conceptualization, Methodology, Software, Data curation, Writing - original draft. **Charles N. Kroll:** Conceptualization, Methodology, Data curation, Validation, Writing - review & editing. **David J. Nowak:** Validation, Writing - review & editing.

## Declaration of Competing Interest

The authors declare no conflict of interest.

## Acknowledgments

This research was supported by the United States Department of Agriculture (USDA) Forest Service with grant 16-DG-11132544-034 recommended by the National Urban and Community Forestry Advisory Council, grant 11-JV-11242308-112 from the USDA Forest Service Northern Research Station, and additional support from the SUNY ESF Department of Environmental Resources Engineering. Special thanks to Robert Hoehn for helping with i-Tree Eco runs. We also thank two anonymous reviewers for their comments and suggestions that helped to improve the manuscript.

## Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.ufug.2021.127062.

## References


Aguaron, E., McPherson, E.G., 2012. Comparison of methods for estimating carbon dioxide storage by Sacramento's urban forest carbon sequestration in urban ecosystems. In: Lal, R., Augustin, B. (Eds.), Ch 3 in Carbon Sequestration in Urban Ecosystems. Springer, New York, NY, pp. 43–71.

Ascough Ii, J., Maier, H., Ravalico, J., Strudley, M., 2008. Future research challenges for incorporation of uncertainty in environmental and ecological decision-making. Ecol. Modell. 219 (3-4), 383–399.

Beck, M.B., 1987. Water quality modeling: a review of the analysis of uncertainty. Water Resour. Res. 23 (8), 1393–1442.

Beven, K., Binley, A., 1992. The future of distributed models: model calibration and uncertainty prediction. Hydrol. Process. 6 (3), 279–298.

Beven, K., Lamb, R., Leedal, D., Hunter, N., 2015. Communicating uncertainty in flood inundation mapping: a case study. Int. J. River Basin Manag. 13 (3), 285–295.

Bodnaruk, E., Kroll, C., Yang, Y., Hirabayashi, S., Nowak, D., Endreny, T., 2017. Where to plant urban trees? A spatially explicit methodology to explore ecosystem service tradeoffs. Landsc. Urban Plan. 157, 457–467.

Boukili, V.K., Bebber, D.P., Mortimer, T., Venicx, G., Lefcourt, D., Chandler, M., Eisenberg, C., 2017. Assessing the performance of urban forest carbon sequestration models using direct measurements of tree growth. Urban For. Urban Green. 24, 212–221.

Bryant, B.P., Borsuk, M.E., Hamel, P., Oleson, K.L., Schulp, C., Willcock, S., 2018. Transparent and feasible uncertainty assessment adds value to applied ecosystem services modeling. Ecosyst. Serv. 33, 103–109.

Chave, J., Réjou-Méchain, M., Búrquez, A., Chidumayo, E., Colgan, M.S., Delitti, W.B., Duque, A., Eid, T., Fearnside, P.M., Goodman, R.C., 2014. Improved allometric models to estimate the aboveground biomass of tropical trees. Glob. Chang. Biol. 20 (10), 3177–3190.

Clark, J.S., 2003. Uncertainty and variability in demography and population growth: a hierarchical approach. Ecology 84 (6), 1370–1381.

Davies, Z.G., Dallimer, M., Edmondson, J.L., Leake, J.R., Gaston, K.J., 2013. Identifying potential sources of variability between vegetation carbon storage estimates for urban areas. Environ. Pollut. 183, 133–142.

Devore, J.L., 2016. Probability and Statistics for Engineering and the Sciences. Cengage Learning, Boston, MA, p. 239.

Draper, D., 1995. Assessment and propagation of model uncertainty. J. R. Stat. Soc. Ser. B 45–97.

Efron, B., 1982. The Jackknife, the Bootstrap, and Other Resampling Plans. SIAM, Philadelphia, PA, p. 92.

Gallagher, M., Doherty, J., 2007. Parameter estimation and uncertainty analysis for a watershed model. Environ. Model. Softw. 22 (7), 1000–1020.

Habte, A., Sengupta, M., Lopez, A., 2017. Evaluation of the National Solar Radiation Database (NSRDB), 1998-2015, NREL/TP-5D00-67722.

Hallegatte, S., 2009. Strategies to adapt to an uncertain climate change. Glob. Environ. Chang. Part A 19 (2), 240–247.

Hanna, S., Russell, A., Wilkinson, J., Vukovich, J., Hansen, D., 2005. Monte Carlo estimation of uncertainties in BEIS3 emission outputs and their effects on uncertainties in chemical transport model predictions. J. Geophys. Res. Atmos. 110 (D1).

Held, I.M., 2005. The gap between simulation and understanding in climate modeling. Bull. Am. Meteorol. Soc. 86 (11), 1609–1614.

Helton, J.C., Johnson, J.D., Sallaberry, C.J., Storlie, C.B., 2006. Survey of sampling-based methods for uncertainty and sensitivity analysis. Reliab. Eng. Syst. Saf. 91 (10-11), 1175–1209.

Hill, M.C., 1998. Methods and guidelines for effective model calibration US geological survey. Water-Res. Invest. Rep. 98–4005, 91.

i-Tree Eco Field Guide (2019). https://www.itreetools.org/support/resources-overview/i-tree-manuals-workbooks. (accessed April 2020).

Leff, M., 2016. The Sustainable Urban Forest: a Step-by-step Approach. Davey Institute/USDA Forest Service.

Lin, J., Kroll, C.N., Nowak, D.J., Greenfield, E.J., 2019. A review of urban forest modeling: implications for management and future research. Urban For. Urban Green., 126366

Lin, J., Kroll, C.N., Nowak, D.J., 2020. Ecosystem service-based sensitivity analyses of i-Tree Eco. Arboric. Urban For. 46 (4), 287–306.

Martin, N., Chappelka, A., Somers, G., Loewenstein, E., Keever, G., 2013. Evaluation of sampling protocol for i-Tree Eco: A case study in predicting ecosystem services at Auburn University. Arboric. Urban For. 39 (2), 56–61.

McHale, M., Burke, I., Lefsky, M., Peper, P., McPherson, E., 2009. Urban forest biomass estimates: is it important to use allometric relationships developed specifically for urban trees? Urban Ecosyst. 12 (1), 95–113.

McPherson, E.G., Simpson, J.R., Xiao, Q., Wu, C., 2011. Million trees Los Angeles canopy cover and benefit assessment. Landsc. Urban Plan. 99 (1), 40–50.

McPherson, E.G., Xiao, Q., Aguaron, E., 2013. A new approach to quantify and map carbon stored, sequestered and emissions avoided by urban forests. Landsc. Urban Plan. 120, 70–84.

McPherson, E.G., van Doorn, N.S., Peper, P.J., 2016. Urban Tree Database and Allometric Equations. Gen. Tech. Rep. PSW-GTR-253. US Department of Agriculture, Forest Service, Pacific Southwest Research Station, Albany, CA, p. 86 p., 253.

Mishra, S., 2009. Uncertainty and sensitivity analysis techniques for hydrologic modeling. J. Hydroinformatics 11 (3-4), 282–296.

Narasimhan, B., Srinivasan, R., Arnold, J., Di Luzio, M., 2005. Estimation of long-term soil moisture using a distributed parameter hydrologic model and verification using remotely sensed data. Trans. Asae 48 (3), 1101–1113.

Nowak, D.J., 1996. Estimating leaf area and leaf biomass of open-grown deciduous urban trees. For. Sci. 42 (4), 504–507.

Nowak, D.J., Crane, D.E., Stevens, J.C., 2006. Air pollution removal by urban trees and shrubs in the United States. Urban For. Urban Green. 4 (3-4), 115–123.

Nowak, D.J., Crane, D.E., Stevens, J.C., Hoehn, R.E., Walton, J.T., Bond, J., 2008a. A ground-based method of assessing urban forest structure and ecosystem services. Aboricult. Urban Forestry 34 (6), 347–358, 34(6).

Nowak, D.J., Walton, J.T., Stevens, J.C., Crane, D.E., Hoehn, R.E., 2008b. Effect of plot and sample size on timing and precision of urban forest assessments. Aboricult. Urban Forestry. 34 (6), 386–390, 34(6).

Nowak, D.J., Greenfield, E.J., Hoehn, R.E., Lapoint, E., 2013. Carbon storage and sequestration by trees in urban and community areas of the United States. Environ. Pollut. 178, 229–236.

Nowak, D.J., Hirabayashi, S., Bodine, A., Greenfield, E., 2014. Tree and forest effects on air quality and human health in the United States. Environ. Pollut. 193, 119–129.

Nyelele, C., Kroll, C.N., 2020. The equity of urban forest ecosystem services and benefits in the Bronx, NY. Urban For. Urban Green. 53, 1–13.

Pace, R., Biber, P., Pretzsch, H., Grote, R., 2018. Modeling ecosystem services for park trees: sensitivity of i-tree eco simulations to light exposure and tree species classification. Forests 9 (2), 89.

Pappenberger, F., Beven, K.J., 2006. Ignorance is bliss: or seven reasons not to use uncertainty analysis. Water Resour. Res. 42 (5).

Peper, P.J., McPherson, E.G., 2003. Evaluation of four methods for estimating leaf area of isolated trees. Urban For. Urban Green. 2 (1), 19–29.

Refsgaard, J.C., van der Sluijs, J.P., Højberg, A.L., Vanrolleghem, P.A., 2007. Uncertainty in the environmental modelling process–a framework and guidance. Environ. Model. Softw. 22 (11), 1543–1556.

Regan, H.M., Colyvan, M., Burgman, M.A., 2002. A taxonomy and treatment of uncertainty for ecology and conservation biology. Ecol. Appl. 12 (2), 618–628.

Rindfuss, R.R., Walsh, S.J., Turner, B.L., Fox, J., Mishra, V., 2004. Developing a science of land change: challenges and methodological issues. Proc. Natl. Acad. Sci. U.S.A. 101 (39), 13976–13981.

Roman, L.A., Scharenbroch, B.C., Östberg, J.P., Mueller, L.S., Henning, J.G., Koeser, A.K., Sanders, J.R., Betz, D.R., Jordan, R.C., 2017. Data quality in citizen science urban tree inventories. Urban For. Urban Green. 22, 124–135.

Salas, J.D., 1980. Applied Modeling of Hydrologic Time Series: Water Resources Publication.

Sengupta, M., Xie, Y., Lopez, A., Habte, A., Maclaurin, G., Shelby, J., 2018. The National Solar Radiation Data Base (NSRDB). Renew. Sustain. Energy Rev. 89 (June), 51–60.

Shashua-Bar, L., Hoffman, M.E., 2002. The Green CTTC model for predicting the air temperature in small urban wooded sites. Build. Environ. 37 (12), 1279–1288.

Situ, S., Wang, X., Guenther, A., Zhang, Y., Wang, X., Huang, M., Fan, Q., Xiong, Z., 2014. Uncertainties of isoprene emissions in the MEGAN model estimated for a coniferous and broad-leaved mixed forest in Southern China. Atmos. Environ. 98, 105–110.
Stas, S.M., Rutishauser, E., Chave, J., Anten, N.P., Laumonier, Y., 2017. Estimating the aboveground biomass in an old secondary forest on limestone in the Moluccas, Indonesia: Comparing locally developed versus existing allometric models. For. Ecol. Manage. 389, 27–34.
Timilsina, N., Beck, J.L., Eames, M.S., Hauer, R., Werner, L., 2017. A comparison of local and general models of leaf area and biomass of urban trees in USA. Urban For. Urban Green. 24, 157–163.
Turner, M.G., Gardner, R.H., 2015. Landscape Ecology in Theory and Practice: Pattern and Process. Springer-Verlag, New York, New York, USA.
Van Breugel, M., Ransijn, J., Craven, D., Bongers, F., Hall, J.S., 2011. Estimating carbon stock in secondary forests: decisions and uncertainties associated with allometric biomass models. For. Ecol. Manage. 262 (8), 1648–1657.
Walker, W.E., Harremoës, P., Rotmans, J., Van Der Sluijs, J.P., Van Asselt, M.B., Janssen, P., Krayer von Krauss, M.P., 2003. Defining uncertainty: a conceptual basis for uncertainty management in model-based decision support. Integr. Assess. 4 (1), 5–17.
Wang, X., Situ, S., Chen, W., Zheng, J., Guenther, A., Fan, Q., Chang, M., 2016. Numerical model to quantify biogenic volatile organic compound emissions: the Pearl River Delta region as a case study. J. Environ. Sci. 46, 72–82.
WHO (World Health Organization), 2008. Uncertainty and Data Quality in Exposure Assessment Part 1: Guidance Document on Characterizing and Communicating Uncertainty in Exposure Assessment Part 2: Hallmarks of Data Quality in Chemical Exposure Assessment. International Programme on Chemical Safety, Geneva, Switzerland.
Wu, Z., Chen, L., 2017. Optimizing the spatial arrangement of trees in residential neighborhoods for better cooling effects: integrating modeling with in-situ measurements. Landsc. Urban Plan. 167, 463–472.
Wu, J., Jones, B., Li, H., Loucks, O.L., 2006. Scaling and Uncertainty Analysis in Ecology. Springer.
Yanai, R.D., Battles, J.J., Richardson, A.D., Blodgett, C.A., Wood, D.M., Rastetter, E.B., 2010. Estimating uncertainty in ecosystem budget calculations. Ecosystems 13 (2), 239–248.
Yanai, R.D., See, C.R., Campbell, J.L., 2018. Current practices in reporting uncertainty in ecosystem ecology. Ecosystems 21 (5), 971–981.
Yanai, R.D., Wayson, C., Lee, D., Espejo, A., Campbell, J.L., Green, M.B., Zukswert, J.M., Yoffe, S., Aukema, J., Lister, A., 2020. Improving uncertainty in forest carbon accounting for REDD+ mitigation efforts. Environ. Res. Lett. 15 (12), 124002.
Zheng, J., Zheng, Z., Yu, Y., Zhong, L., 2010. Temporal, spatial characteristics and uncertainty of biogenic VOC emissions in the Pearl River Delta region, China. Atmosph. Environ. 44 (16), 1960–1969.